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RESEARCH ARTICLE

Are European Farms Equally Efficient? What Do Regional FADN Data on Crop Farms Tell Us?

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Abstract

The study analyzes productive efficiency of crop farming in the EU. We use publicly available data on crop farming from FADN database. Standard efficiency measurement techniques based on frontier analysis indicate that the representative farms provided in the database are fully efficient, even though there is ample evidence in the literature that this is highly unlikely. We find that this is a consequence of overly restrictive assumptions about the compound error in standard SF models. The efficiency benchmark, based on the best model given data with generalized error specification, reveals substantial differences in crop farming efficiency in the EU.

Keywords: Crop farming; fat-tailed distributions; model misspecification; stochastic frontier analysis; wrong skewness

JEL classifications: C11; O47; O13

1. Introduction

Field crops provide the principal source of food supply in the world. They are quite diverse in terms of products and manufacturing processes. Food and Agriculture Organization of the United Nations (FAO) classifies the European Union as part of the European and Central Asian agricultural region. According to the report by OECD-FAO (2022) the major crop producers in this region are the European Union, the United Kingdom, Russia, Ukraine, and Kazakhstan. As far as the performance of the EU Member States is considered, it should be noted that generally the production is growing in the EU. According to the European Commission (2022) the main producers are France (which harvested 66.9 million tonnes of cereals in 2021, 22.5% of the EU total), Germany (with 42.4 million tonnes of cereals, 14.3% of the EU total) and Poland (34 million tonnes, which is 11.4% of the EU total).

The report by OECD-FAO (2022) states that while the European and Central Asian agricultural region has successfully managed with challenges of the COVID-19 pandemic – i.e., logistical bottlenecks, workforce shortages, changes to the quantity and composition of demand – the 2022 Russian aggression of Ukraine brings serious uncertainty to the future of this region. The report enlists three reasons for this. First, Russia is a major supplier of inputs for agricultural production to Europe and Central Asia. Russia is the world's top exporter of nitrogen fertilizers, the second leading exporter of potassic fertilizers, and the third leading exporter of phosphorus fertilizers, accounting for over 15% of total global fertilizer exports in 2020. The 2022 Russian invasion of Ukraine has brought huge uncertainty in terms of availability of Russian energy and fertilizers globally. Second, Russia and Ukraine are both important producers and exporters of arable crops in the world. Russia and Ukraine account for about 10 and 3% of global wheat production, respectively, at the same time being the first and the fifth largest wheat exporters, accounting for 20 and 10% of global exports, respectively. Russia and Ukraine account for 20% of global barley production and are the third and fourth largest exporters, respectively. Ukraine is the world's largest producer of sunflower seed, followed by Russia. Together, they account for more than 50% of the global production. The importance of Ukraine to the global agricultural markets comes also from the fact that it is the largest non-GMO exporter and an important exporter of organic feed. Third, the two countries are key importers of several agri-food products from other countries in the region, which may find it difficult to locate alternative markets. Even though Russia's war against Ukraine has disrupted its agricultural sector, Ukraine remains a vital exporter to other agricultural markets.

All the abovementioned issues threaten food security in the EU. In the light of scarce resources, which additionally can be unavailable, the enquiry into the efficiency of the EU's agriculture is even more important than before. It seems that only efficiency gains in crop production can keep real agricultural prices relatively stable. Furthermore, it is important to note that there is a common agricultural policy in the European Union for all Member States, and thus EU-wide benchmarks are important for adequate policymaking at the European Commission.

The goal of this research is to provide a credible, state of the art benchmark for the efficiency of crop farming in the EU. To do this, we adopt Stochastic Frontier Analysis (SFA), which is often used in performance-based policymaking. We start with standard stochastic frontier (SF) models, i.e., normal-half-normal and normal-exponential, which are the workhorses for efficiency and productivity analysis nowadays. We find the residuals to be positively "skewed" which is predominantly interpreted in SFA as lack of inefficiency or, in other words, full – or almost full – efficiency. This is an obvious culprit of such analyses as it is in stark contrast with common knowledge in the field of crop farming. We propose to look at the "wrong skewness" problem in a different way, i.e., as an artifact of over-restrictive assumptions about the compound error term in "classic" SF specifications (half-normal, exponential, gamma, etc.). Our motivation comes from the fact that these assumptions are usually set due to pure computational convenience rather than any theoretical considerations. To deal with the problem – and the unfeasible full efficiency it produces – we apply the generalized *t* – generalized beta of the second kind model (GT-GB2 hereafter), which is the most generalized parametrization of an SF model to this date (Makieła and Mazur, 2022). We find that, unlike in standard SFA, the most probable model given the data indicates substantial differences in efficiency across the EU.

The remaining part of the paper is as follows. Section 2 reviews literature on crop farming with a focus on comparative analysis of productivity and productive efficiency. Section 3 discusses methodology used in the study while Section 4 discusses the data used. Study results are presented in Section 5 and key findings are discussed in Section 6. Conclusions are provided in Section 7.

2. Literature review

There are many studies on technical efficiency for selected farm sectors using farm-level data (Dakpo et al., 2022; Emvalomatis, 2012; Pisulewski and Marzec, 2022; Skevas et al., 2018). Most of the research is done using data from a single country. International comparisons based on farm-level data are far less common. Hence, it is still not fully explored what the performance of the sector is relative to similar sectors in other countries. Probably, the first study to do so was by Zhu and Oude Lansink (2010) who compared technical efficiency of crop farms between Germany, the Netherlands, and Sweden. Barnes and Revoredo-Giha (2011) employed a metafrontier approach to compare technical efficiency of four farm types (specialist cereals, oilseed and protein crops, specialist dairy, field cropping, and mixed farms). Their analysis covered 11 countries (Belgium, Denmark, France, Germany, Hungary, Ireland, Italy, the Netherlands, Poland, Spain, and the UK), and the results indicated Polish crop farms to be the most efficient. An example of bilateral comparison is Latruffe et al. (2012), who compared technical efficiency of crop and dairy farms between France and Hungary. In the first stage, the authors calculated the efficiency of farms with respect to the country-specific frontier and in the second stage with respect to the metafrontier. They have found that Hungarian crop farms are more efficient than French ones, given the metafrontier.

Rizov et al. (2013) analyzed productivity in the EU-15 Member States (Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxemburg, Netherlands, Austria, Portugal, Finland, Sweden, United Kingdom). They employed a panel that covered 1990–2008. The goal of that study was to estimate the total factor productivity measures at farm level, within six (FADN) farm-type samples for each country. Six small, north European countries (Belgium, Denmark, Ireland, Finland, the Netherlands, Sweden) showed productivity decline, while the three largest EU-15 countries, i.e., Germany, France and the UK showed small productivity growth. The highest average annual productivity growth was recorded by the south European countries, i.e., Italy, Portugal and Spain.

Čechura et al. (2015) compared efficiency of cereal farms in 24 European Union Member States. The authors used farm-level data to estimate parameters of stochastic frontier models separately for each country. In the second step, they employed a metafrontier approach. They found technical efficiencies calculated at the regional level (NUTS 2) to be between 0.89 and 0.92. Latruffe et al. (2017) also used farm-level data to investigate the technical efficiency in nine EU countries: Belgium, Denmark, France, Germany, Ireland, Italy, Portugal, Spain, and the United Kingdom. Biagini et al. (2023) focused on field crop farms in six EU countries, namely France, Germany, Italy, Poland, Spain and the UK in 2008–2018. They were mainly interested in understanding how CAP subsidies affect farms productivity, but provided the total factor productivity (TFP) measures too. Their results show that in the covered period the highest TFP change was experienced by the UK and France, followed by Germany, Italy, Spain and Poland.

There were several studies that used Farm Accountancy Data Network (FADN) public database (European Commission, Directorate-General for Agriculture and Rural Development, 2020). For example, Błażejczyk-Majka et al. (2012) analyzed if more specialization and a higher class of economic size results in higher technical efficiency for the farms from the new and old EU Member States. The study was based on 80 FADN regions from 15 EU Member States (11 old and 4 new Member States) in 2004–2007. They analyzed the technical efficiency of field crops and mixed farms using Data Envelopment Analysis (DEA). They found that the technical efficiency of crop farms from the old Member States was higher than those from the new Member States. Moreover, their results indicated that the large farms were more efficient in the old Member States than in the new ones. The same methodology was employed by Gerdessen and Pascucci (2013). However, instead of traditional inputs, they used economic and social indicators to point out the sustainable agricultural regions in the EU. They analyzed 252 European regions under five scenarios, where the scenarios differed in terms of the weights assigned to the dimension of sustainability. Under the scenario, in which the economic indicators were the most important the authors found that 23 regions were efficient under constant returns to scale and 35 under variable returns. These were mainly regions from Germany (five regions), the Netherlands (four regions), Austria (three regions), Sweden (three regions) and the UK (three regions). Špička (2014) analyzed the technical efficiency of mixed crop and livestock farms using DEA method with variable returns to scale. The author used cross-sectional data on 101 EU regions from 2011. He identified 56 efficient regions and 45 inefficient ones. Špička (2014) pointed out that the farms in efficient regions were on average large. Moreover, all four regions in Poland were in the group of inefficient regions.

Quiroga et al. (2017) employed data from FADN at NUTS 2 level. They analyzed data, which covered 98 regions from ten EU Member States in 1996–2009. Quiroga et al. (2017) estimated model for beta convergence of technical efficiency for the whole period and for the two seven-year subperiods. Their results indicated the existence of beta convergence for the whole period. The same result was obtained for the second sub-period, while the first sub-period showed a divergence in technical efficiency.

The subsequent study based on regional FADN data was Martinho (2017) who analyzed the efficiency and returns to scale in the EU regions in 2013 using DEA, though the study did not specify the agricultural type of these farms. The regions identified as efficient ones were mainly in France, Belgium, the Netherlands, Denmark, Austria and Sweden. There was only one fully efficient region in Italy (Aosta) and two in Spain (Asturia and Cantabria).

Garrone et al. (2019) investigated 213 EU regions from all 27 member states in 2004–2014, with the total of 1971 observations. They used the data aggregated at NUTS 2 level with exception of Denmark, Germany, Slovenia and the United Kingdom, for which they used NUTS 1 level. They did not consider separate agricultural sectors, since they used Cambridge Econometric Regional Database, in which agriculture is treated as one sector. They found that there is a conditional beta convergence in terms of labor productivity. The speed of convergence is higher for the New Member States (3.7–20.2%) than for the Old Member States (5.4–9.7%). Garrone et al. (2019) did not find evidence in favor of σ convergence.

Marzec and Pisulewski (2020) used FADN regional data on crop farms, which are similar to the data used in this study. They applied the Random Parameters stochastic frontier model to account for the technology heterogeneity between the so-called representative farms. They concluded that the representative farms in the EU regions are almost equally efficient. This result, however, was likely because the OLS residuals from their production function were positively skewed. This is known as the "wrong skewness" problem in SFA, which was also identified in FADN data by Staniszewski and Borychowski (2020). The authors estimated four types of SF models, i.e., translog and Cobb-Douglas production function in a fixed and random effects framework, separately for each of the six size classes of farms (they considered all types of agricultural production). They found that only for the three economic sizes: 25–50, 50–100 and 100–500 [thousand EUR of standard output] it is possible to estimate (in)efficiency. Although the study employed a different approach than Marzec and Pisulewski (2020), it also indicated very high average technical efficiency.

The last group of studies that can be distinguished are studies based on country-level data. One of the recent studies is the work of Baráth and Fertő (2017). They used the Färe-Primont TFP index to analyze the state of development of the European agriculture sector at the country level and analyzed productivity convergence across Member States. They found that during the studied period (2004–2013) TFP level was higher for old Member States than for the new Member States. However, in terms of TFP change they found that the trend was increasing over time for the new Member States and decreasing for the old ones. They also analyzed productivity convergence across the EU and concluded that agricultural TFP is converging, though the rate of this convergence is rather slow. Acosta and Santos-Montero (2019) presented a global comparison of TFP change in three agricultural production systems: crops, ruminants and monogastrics. Crops reported the highest TFP growth level, and the two best performing regions were Brazil and Germany. Kijek et al. (2019) measured country-level TFP change in agriculture in 25 EU countries in 2004–2016. Using the Färe-Primont index they found that the TFP level was relatively lower in the New Member States than in most EU-15 states. They found convergence in agricultural productivity almost in all EU Member States (except Belgium and the UK). However, the convergence between EU-15 was stronger than between the New Member States. Wimmer and Dakpo (2023) also used country-level data on agricultural outputs and inputs for 25 countries in 2000–2019. Their results obtained from A-DEA index showed that at the individual country level, Latvia achieved the largest TFP gains (+74%) followed by Belgium (+73%), Romania (+58%) and Poland (+47%), while the global Malmquist TFP index indicated that the largest TFP gains were achieved by Slovakia (+64), Hungary (+50%), Belgium (+34%) and Finland (+27%).

To sum up, most studies in the field focus on farm-level data and on a single country. For international comparisons, whenever farm-level data are used the metafrontier approach is usually employed. When country-level data or regional-level data are used, the technology frontier is usually common for the decision-making units. However, such studies mainly use DEA. Hence, our research contributes in several ways. First, we use stochastic frontier analysis as it seems more adequate for crop production, which can be significantly affected by random disturbances such as weather. Second, we show that the problem of wrong skewness of the OLS residuals, quite common in applied SFA, can be solved within SFA framework via proper generalization of the compound error term. Finally, we compare the technical efficiency of the EU regions based on *publicly available* regional data from FADN (European Commission, Directorate-General for Agriculture and Rural Developments, 2020), which makes the research replicable.

3. Methodology

We start by considering a standard SF parametrization based on a translog approximation of an unknown production function (model m_0):

$$y_{it} = \beta_0 + \beta_1 t + \sum_{j=1}^{J} \beta_{j+1} x_{it,j} + \sum_{j=1}^{J} \sum_{g \geq j}^{J} \beta_{j,g} x_{it,j} x_{it,g} + \varepsilon_{it}, \tag{1a}$$

where β is a vector of parameters, y_{it} is the log of output, $x_{it,1}$ is buildings and machinery (in logs; next to parameter β_2), $x_{it,2}$ is labor (in logs; β_3), $x_{it,3}$ is materials (in logs; β_4) and $x_{it,4}$ is area (in logs; β_5), $\varepsilon_{it} = v_{it} - u_{it}$ is the compound error, $J = 4$ represents the number of production inputs, $i = 1,..,N$ and $t = 1,..,T$ are indices for a representative farm and a year respectively. The component v_{it} of ε_{it} represents a standard *i.i.d.* observation error (symmetric disturbance) with symmetric and unimodal distribution. The component u_{it} represents inefficiency and, as such, it is treated as an *i.i.d.* latent variable, which takes only nonnegative values. Assumption that $u_{it} = 0$ (i.e., $\varepsilon_{it} = v_{it}$) reduces the SF model to a standard regression, here labeled as "non-SF." Parameter β_1 next to trend variable (t) represents a linear neutral technical change (in logs), which is a reasonable approximation of the technical change when the panel is not large with respect to T. Other common strategies to model technical change are:

1. Add to m_0 variable time squared (t squared) and allow trend variable to interact with logs of inputs, meaning that we treat trend the same way as other production factors (model m_1):

$$y_{it} = \beta_0 + \beta_1 t + \sum_{j=1}^{J} \beta_{j+1} x_{it,j} + \sum_{j=1}^{J} \sum_{g \geq j}^{J} \beta_{j,g} x_{it,j} x_{it,g} + \gamma_1 t^2 + \sum_{j=1}^{J} \gamma_{j+1} x_{it,j} t + \varepsilon_{it}, \tag{1b}$$

where $\gamma_1, \gamma_2, \ldots, \gamma_{J+1}$ are the additional parameters.

2. Add to m_0 just t squared (i.e., m_1 with $\gamma_j = 0$ for $j = 2, \ldots, (J{+}1)$; model m_2).
3. Add to m_0 the fixed time effects (λ_t) instead of linear or quadratic trend (model m_3)

$$y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_{j+1} x_{it,j} + \sum_{j=1}^{J} \sum_{g \geq j}^{J} \beta_{j,g} x_{it,j} x_{it,g} + \lambda_t + \varepsilon_{it}, \tag{1c}$$

where year 2004 is set as the reference period ($\lambda_{t=1} = 0$). One could also take any combination of the abovementioned frontier parametrizations m_1 and m_3 that maximizes model's explanatory power (e.g., marginal likelihood), though we should note that the total number of all possible specifications is $L = 2^{34} - 2$ (34 being the maximum number of explanatory variables by

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combining m_1 and m_3, less the case with trend and *all* time effects λ_t, which is not feasible due to collinearity, and less the "empty" model case). This may be difficult to compute in an acceptable timeframe, especially under nonstandard assumptions about the stochastic term. We return to the discussion about the production frontier specification in Section 5.1.

Under the accepted production function specification for crop farming, our goal is to adequately model both, u_{it} and v_{it} since this will have an impact on efficiency measurement. Standard parametric SFA models may have potentially restrictive assumptions about v_{it} and u_{it}, and thus some researchers suggest to use nonparametric SFA to cope with this issue (Assaf et al., 2021). We follow a different path and incorporate the framework proposed by Makieła and Mazur (2022) in order to find the optimal parametric specification for v_{it} and u_{it}, and thus the compound error ε_{it}. Let v_{it} follow a generalized t distribution, GT:

$$f_{GT}(\mathrm{v_{it}};\sigma_\mathrm{v},\nu_\mathrm{v},\psi_\mathrm{v}) = \frac{1}{\sigma_\mathrm{v}}\frac{\psi_\mathrm{v}}{B\left(1/\psi_\mathrm{v},\nu_\mathrm{v}/\psi_\mathrm{v}\right)2\nu_\mathrm{v}^{1/\psi_\mathrm{v}}}\left[\frac{1}{\nu_\mathrm{v}}\left(\frac{|\mathrm{v_{it}}|}{\sigma_\mathrm{v}}\right)^{\psi_\mathrm{v}}+1\right]^{-(1+\nu_\mathrm{v})/\psi_\mathrm{v}}, \tag{2}$$

where $B(.,.)$ denotes the beta function, σ_v is a scale parameter, ν_v is a shape parameter that "controls" the tails (similar to the degrees of freedom in t distribution) and ψ_v is a shape parameter that determines the shape of the distribution around the mode (i.e., for $\psi_\mathrm{v} = 1$ the distribution is similar to Laplace, for $\psi_\mathrm{v} = 2$ it is similar to normal; $\psi_\mathrm{v} > 1$ implies shapes, which are more flattened compared to normal). Inefficiency (u_{it}) follows the generalized beta distribution of the second kind, GB2 (Harvey and Lange, 2017):

$$f_{GB2}(\mathrm{u};\sigma_\mathrm{u},\nu_\mathrm{u},\psi_\mathrm{u},\tau) = \frac{1}{\sigma_\mathrm{u}}\frac{\psi_\mathrm{u}}{B\left(\tau/\psi_\mathrm{u},\nu_\mathrm{u}/\psi_\mathrm{u}\right)\nu_\mathrm{u}^{\tau/\psi_\mathrm{u}}}\left(\frac{\mathrm{u}}{\sigma_\mathrm{u}}\right)^{\tau-1}\left[\frac{1}{\nu_\mathrm{u}}\left(\frac{\mathrm{u}}{\sigma_\mathrm{u}}\right)^{\psi_\mathrm{u}}+1\right]^{-(\tau+\nu_\mathrm{u})/\psi_\mathrm{u}}, \tag{3}$$

where the additional parameter τ determines the behavior of the distribution at the mode (i.e., at zero). That is, if $\tau = 1$ the distribution reduces to half-GT, $\tau < 1$ implies lack of continuity at the mode, and if $\tau > 1$ the distribution is bimodal. The above model encompasses virtually all known SF model specifications and many new ones. The list of selected models used in the study, based on the GT-GB2 specification, is provided in Table 1. The last column provides labels, which are later used throughout the paper. Also following Makieła and Mazur (2022), we assume independence between u and v. Though in theory this assumption could be relaxed it would undoubtedly lead to identification problems in most of the SF specifications considered (see, e.g., Das and Bandyopadhyay, 2008).

Makieła and Mazur (2022) present two ways to estimate the GT-GB2 model: (i) an exact approach based on Bayesian inference and (ii) an approximate one based on Maximum Likelihood. We use Bayesian inference because we wish to take advantage of Bayes factors for determining the optimal model specification for v_{it} and u_{it} given data. The Bayes factor (BF) is a ratio of marginal likelihoods $p(y)$ of two competing model specifications, M_1 and M_2, and it is equal to the posterior odds divided by prior odds:

$$BF = \frac{\mathrm{p}(y|M_1)}{\mathrm{p}(y|M_2)} = \frac{\mathrm{p}(M_1|y)}{\mathrm{p}(M_2|y)} \div \frac{\mathrm{p}(M_1)}{\mathrm{p}(M_2)}. \tag{4}$$

If $BF > 1$ the data favor model M_1 over M_2; if $BF < 1$ model M_2 is preferred. Also, under equal prior odds ($\mathrm{p}(M_1) = \mathrm{p}(M_2)$) BF is equal to posterior odds. Equal prior odds mean that *a priori* we do not favor any specification. We use this approach (equal model prior odds) throughout the paper, and thus the reported Bayes factors in the empirical section can also be viewed in terms of posterior odds. Marginal likelihood is obtained via Laplace-type approximation with parameters' distributions transformed to an unconstrained space where applicable (i.e., we do not transform β's). As Makieła and Mazur (2022) point out, such transformations are necessary because Laplace-type approximations work better in an unconstrained parameter space. This approach has been

Table 1. List of selected model specifications and their labels

$p_v(v; .)$	$p_u(u; .)$	Restrictions in GT-GB2 SF	Model label
Generalized *t*	GB2	None	GT-GB2
normal	half-normal	$\nu_u, \nu_v \to \infty, \psi_u = \psi_v = 2, \tau = 1$	N-HN
normal	exponential	$\nu_u, \nu_v \to \infty, \psi_u = 1, \psi_v = 2, \tau = 1$	N-EX
Student's *t*	half-Student's *t*	$\psi_u = \psi_v = 2, \tau = 1$	T-HT
Student's *t*	half-normal	$\nu_u \to \infty, \psi_u = \psi_v = 2, \tau = 1$	T-HN
Student's *t*	half-generalized *t*	$\psi_v = 2, \tau = 1$	T-HGT
Laplace	half-normal	$\nu_u \to \infty, \psi_u = 2, \psi_v = 1, \tau = 1$	LP-HN
Laplace	half-Student's *t*	$\psi_u = 2, \psi_v = 1, \tau = 1$	LP-HT
Laplace	half-GED	$\nu_u \to \infty, \psi_v = 1, \tau = 1$	LP-HGED
Laplace	half-generalized *t*	$\psi_v = 1, \tau = 1$	LP-HGT
Generalized *t*	Exponential	$\nu_u \to \infty, \psi_u = 1, \tau = 1$	GT-EX
Generalized *t*	half-normal	$\nu_u \to \infty, \psi_u = 2, \tau = 1$	GT-HN
Generalized *t*	half-Student's *t*	$\psi_u = 2, \tau = 1$	GT-HT
Generalized *t*	half-GED	$\nu_u \to \infty, \tau = 1$	GT-HGED
Generalized *t*	half-generalized *t*	$\tau = 1$	GT-HGT
Generalized *t*	gen.-gamma	$\nu_u \to \infty$	GT-GG
normal	–	$\nu_v \to \infty, \psi_v = 2$	non-SF

tested against more complex methods, e.g., *corrected arithmetic mean* estimator proposed by Pajor (2017), and proven to be comparably accurate (differences were less than a decimal point of $\ln(p(y))$.

Based on Makieła and Mazur (2022) we use the following priors for the GT-GB2 model:

$$\sigma_v, \sigma_u \sim GG(0.5, 1, 1), (\psi_v - 0.1) \sim GG(2, 1, 1), (\psi_u - 0.1) \sim GG(30, 1, 1),$$

$$\tau \sim U(0.05, 1), (\nu_u - 2) \sim GG(30, 1, 1), (\nu_v - 2) \sim GG(30, 1, 1)$$

$$\beta \sim t_k(3, 0_k, 10I_k) \tag{5}$$

where $U(a,b)$ is the uniform distribution between a and b, $t_k(\nu, \mu, A)$ is the multivariate t distribution with degrees of freedom ν, $k\times 1$ location vector μ and $k\times k$ precision matrix A, $GG(\sigma, \tau, \psi)$ is the generalized gamma distribution. Different priors are used for ψ_v and ψ_u, since allowing for $\tau < 1$ implies that the role of the two is somewhat different. The priors in special cases (nested models) are obtained by adequate conditioning, which reflects the model-reducing restrictions and facilitates prior coherence between all models considered. Characteristics of the marginal prior distributions for efficiency, u_{it} and v_{it} in all models are provided in Appendix A. Metropolis-Hastings type samplers for all models are initialized using maximum posterior estimates and an initial run of 50 thousand draws is performed to confirm convergence and mixing properties. Second – final – run, based on which posterior statistics are calculated, takes 301 thousand draws, discarding first one thousand due to sampler's burn-in phase.

4. The data

The dataset used for the analysis is from the Farm Accountancy Data Network (FADN), which contains information on agricultural production in the European Union. It covers a subgroup of farms that reflect the specified characteristics exemplified in a target population of the EU Member States, i.e., region in the country (location), economic size and type of farming; see, e.g., Janssen et al. (2009).

To evaluate the financial condition of farms, the EU requires reasonably detailed data on many individual farms which is currently not widely available (i.e., individual FADN data do exist, but their access is restricted due to confidentiality reasons). However, there are publicly available data, which are aggregated at the region and size scale (European Commission, Directorate-General for Agriculture and Rural Development, 2020). Thus, it allows us to conduct comparative analysis at the country/region level even though in the literature, the analysis of the decision-making units is mostly performed on individuals. According to FADN methodology, the crop farms we investigate belong to the group marked as TF8 = 1, which contains specialist cereals, oilseeds, protein crops, and general field cropping. Therefore, horticulture production, fruit farms and vineyards are not subject to the analysis.

In this study, we refer to the concept of a *representative* farm, which is a known concept in economics literature (Carter, 1963; Sharples, 1969). A representative farm, also known as an average farm, or a typical farm is one that is typical of a group of farms in the region, which it is said to represent. According to FADN, a representative farm is defined as the average value from all farms in the sample, i.e., its resources are measured as the weighted mean (or as the median of the distributions) of the observed values obtained from agricultural holdings covered by the FADN system. The methodology of FADN enables us to extrapolate the economic results obtained from the agricultural farms included in the sample to the agricultural sector as a whole. Also, the definition of regions in FADN is slightly different from NUTS districts. For example, some FADN regions consist of several NUTS 2 regions, while others are similar to each other.

We use aggregated annual data on crop production for the period 2004–2017, which are representative at the regional scale and comparable across country. Additionally, farms are divided into different size groups, which results in a lower degree of aggregation. Thus, a representative farm is constructed as a separated group of agricultural holdings, which operate in a region and belong to one of the six economic size classes, depending on the weighted value of their standard output (the total value of all production). In other words, a representative farm represents a given region with a given revenue. There are some practical problems with aggregated data that, among other things, affect the availability of information to researchers. Each group of farms must have at least 15 units because anonymity and data protection are required, and thus sometimes there are missing data for a given region of the EU, period or class of farm size, especially for the smallest and the biggest farms. For this reason, missing data problem affects countries with many small regions, e.g., Belgium, Bulgaria, France and Spain. Some countries cover only one region, e.g., the Czech Republic, Denmark, Estonia, Lithuania, Latvia, Malta, Netherlands, Austria, Sweden, Slovakia and Slovenia. For Hungary and Portugal, in which complete regional data were not available for the whole period, data aggregated at the country level were used. Finally, Croatia, Cyprus, Ireland and Luxembourg, which are categorized as countries with very small crop areas, have been excluded from the research investigation.

The analysis is based on unbalanced panel data from 404 representative crop farms located in 99 regions of 24 countries of the EU and observed over a period of $T = 14$ years (2004–2017). Thus, the total number of observations is 4446 and, on average, 11 periods per farm. Representative farms were distinguished in terms of the value of gross sales (standard output, SO), i.e., six economic classes were defined as follows: the lowest class means farms' sales ranged from 2000 to 8000 euros, the next group (2) €8,000–25,000, (3) € 5,000–50,000, (4) €50,000–100,000, (5) €100,000–500,000, and the largest agricultural holdings are included in the last group (6) if SO is greater or equals 500,000 euros annually.

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The choice and construction of the variables to be included in the production function is based on other studies, in which FADN data have been used (Bojnec and Latruffe, 2009; Latruffe et al., 2004; Marzec and Pisulewski, 2019; Zhu and Oude Lansink, 2010). In crop agriculture, farmers derive their main income from the sale of wheat, rye, barley, oats, triticale, maize, other cereals, potatoes, sunflowers, sugar beet, rapeseed, hops, tobacco, and other industrial crops. The output is specified as the deflated total net farm revenue from sales, excluding the value of feed, seeds, and plants produced within the farm. The monetary values of output have been deflated (at 2004–2006 average prices) using price indices provided by the Food and Agriculture Organization (FAO) of the United Nations (United Nations, 2022). Specifically, the following price indices were used: cereals, oil plants, and potatoes, and the price indices of total plant production, livestock production, and vegetables. The last two indicators were used because vegetables and livestock were an additional source of income for farmers located in some regions of Italy, Germany and France. The time series indices are available on the country level, and they enable accurate calculations of deflated values for inputs and agricultural products.

Four categories of input are used in the model. Fixed capital is considered in the traditional sense as buildings and fixed equipment belonging to the holder, mobile agricultural machines (e.g., tractors, harvesters, sprayers, lorries), irrigation equipment. Materials and services are the aggregate of components such as seeds and plants, fertilizers, crop protection, crop and livestock specific costs and energy. These two monetary-based inputs are deflated using wholesale producer prices for intermediate goods in industry available at Eurostat (at 2005 prices). For materials, the indices were applied to each country separately. Total labor is measured in natural units, i.e., total hours worked. This measure includes both hired and family labor declared by the farmer during the interview. Finally, total utilized agricultural area (in hectares) refers to the owned and rented land.

Detailed information about the dataset and the number of representative farms that characterize different groups of the farming population is provided in Appendix A (Table A1). Italy, Spain, Romania, France, Germany, Bulgaria, Poland, and Greece belong to the group of countries with the largest number of observations compared to other EU Member States. As expected, Slovenia and Malta are at the bottom of this ranking. Also, Italy stands out from the rest of the countries.

Summary statistics of the explained and explanatory variables as well as their names and labels used in the research are provided in Appendix A (Table A2). The countries which are the largest crop producers are Netherlands, Denmark, Belgium, United Kingdom, Slovakia, and Germany, whereas the smallest producers are Malta, Slovenia and Greece. The statistics may sometimes differ from aggregated data at the country level or from the official data from the governmental statistical institutions due to missing data mentioned earlier. This is also because we consider disaggregated data for the regions of the EU.

When considering the sample variability of inputs, we see that these factors have substantially different variation, which can affect point estimates and standard errors of production elasticities. The set of inputs is characterized by a large spread of the coefficient of variation (CV) defined by the ratio of the sample standard deviation to sample mean and averaged over all farms (see Table A2; Appendix A). The smallest value of this indicator is for land (0.15) and the highest is for buildings and machinery (0.27). CV measure is 0.16 for labor and 0.19 for materials. The differences become even more apparent when we compare economic sizes of farm groups. For example, we find that the CV measure for the area of land in the largest regions is even lower ($CV = 0.1$) compared to the smallest and small farms ($CV = 0.16$ for size $= 1$ and size $= 2$). The highest values of CV are for buildings and machinery with farms' size 1 and 2 (0.31–0.32). All in all, the above results indicate that land input may be quasi-fixed, at least in the short-run and in the largest regions in terms of economic size.

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5. Results

5.1. Optimal model search and its impact on efficiency detection

Our model search strategy is based on two premises. First, model specifications are compared using Bayes factors, which are obtained here *exactly* as ratios of the marginal likelihoods (for any given two competing models); see Eq. 4. Under equal prior odds, this directly translates to posterior odds, which means that we do not prefer any specification and assume that all models are *a priori* equally probable. Second, prior coherence is maintained for all models (see Section 3). This means that our model search is purely data-driven, i.e., the differences in the results are driven by the differences in sampling models, not by the prior specification.

Normally, one would take a standard SF model (frontier m_0), such as normal-half-normal (N-NH) or normal-exponential (N-EX) and carry out efficiency analysis. In doing so, however, we find that the efficiency estimates among representative farms are very high and that there is hardly any variation. The mean efficiency score in N-HN model is 0.944 with a standard deviation of 0.044, and 0.955 (0.044) in case of N-EX. Similar results with FADN data were also obtained by Marzec and Pisulewski (2020) and Staniszewski and Borychowski (2020). It is noteworthy that such an outcome was obtained although the two studies employed methodologies that account for technology heterogeneity, i.e., random coefficient SF model and "true" fixed effects SF model, respectively. These results point towards the notion of full efficiency of the analyzed farms. In fact, the calculated Bayes factors are decisively against the hypothesis of inefficiency component in the analyzed production process (BF $= 0.005$ for N-HN specification and 0.0001 for N-EX; see Appendix B for more results based on m_0 specification). Indeed, this is reaffirmed by "classical" SF estimators, which also point towards "full" efficiency due to "wrong skewness of the residuals" error. For a practitioner to learn that farms across Europe are relatively equally (fully) efficient is just nonsense, especially as there is ample evidence against it in the literature (see Section 2). Sometimes wrong skewness can be caused by a small sample size and there are ways to handle this (see, e.g., Badunenko and Henderson, 2024). However, this study covers 4446 observations.

Data aggregation may also, in theory, affect the skewness of the compound error. For example, if the underlying distribution of inefficiency for individual farms is either half-normal or exponential (i.e., distributions with location parameter at zero) the resulting inefficiency distribution for a representative farm may follow truncated-normal or gamma distribution respectively with location parameter above zero. At its extreme, this may lead to inefficiency distributions being similar in shape to the random disturbance (v), and thus practically non-identifiable. Though there is no simple way to check this theory without access to data on individual farms, we can, e.g., estimate the normal-truncated-normal SF model and check if the mean of the underlying normal distribution of inefficiency is significantly above zero (i.e., before its truncation at zero). This way the data may reveal some evidence in favor, or against, the hypothesis that inefficiency distribution is indeed close to normality. The estimated mean in such model is significantly below zero ($E(u|\text{data}) = -1.84$; standard error: $SE(u|\text{data}) = 0.64$), which indicates that after truncation the distribution of inefficiency is rather exponential than normal. Our findings are similar if we take the normal-gamma SF model instead. The case of a "standard" monotonic, non-increasing shape of inefficiency distribution ($\tau = 1$) is within the 90% confidence interval ($CI_{0.9} = (0.99, 4.39)$; $E(\tau|\text{data}) = 2.69$; $SE(\tau|\text{data}) = 1.1$), and makes the symmetric inefficiency hypothesis rather unlikely. Finally, it is worth noting that data aggregation is a standard practice for most, if not all, regional (e.g., Garrone et al., 2019) and country-level analysis (e.g., Wimmer and Dakpo, 2023), and the fact that our data do not support the abovementioned hypothesis may be simply because inefficiency distribution of the underlying farms is unlikely to be half-normal, nor exponential/gamma (see, e.g., Tsionas, 2017). Hence, we continue our investigation with a note that we investigate the representative farms, which are aggregates of the individual farms (i.e., their aggregated representatives based on FADN methodology), and thus their distribution of inefficiency may differ from that of individual farms.

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To this end, the conclusion is that the models used so far fail to detect the underlying inefficiency of the analyzed process. Usually, one would start refining the technology frontier by adding additional effects customary to panel data (individual group-specific effects, persistent inefficiencies etc.; see., e.g., Makieła, 2017) or by removing nuisance data points or both, to "persuade" the residuals to behave properly, i.e., to have "proper" OLS skewness under the "standard" stochastic structure of the model. The reader should note, however, that methodologies which account for heterogeneity have already been applied to FADN data with no impact on the key issue, i.e., very high efficiency scores with hardly any variation, which is the consequence of wrong skewness of the OLS residuals (e.g., random coefficient SF model or "true" fixed effects SF model; see Marzec and Pisulewski, 2020; Staniszewski and Borychowski, 2020). Furthermore, frontier heterogeneity – introduced, e.g., directly via individual effects – would make cross-section farm efficiency benchmark much more cumbersome as every representative farm would have a different frontier. This may turn out to be counterproductive from a policymaking perspective, e.g., if a policymaker needs efficiency terms to be defined "broadly" and account for all crop farming aspects that are unobserved directly. Hence, we would argue that accounting for possible heterogeneity in efficiency benchmarks is as much of a policy decision (what the regulator wants the efficiency not to account for) as it is academic.

One aspect worth considering is how to model production frontier in terms of technical change over time because apart from positively skewed OLS residuals, we also get a negative average technical change in the basic frontier specification (m_0; see Section 3). This may be either due to increasing ecological pressure from the legislator (i.e., technological bias), or due to interlinked crises that affected the EU around the analyzed period (e.g., the global financial crisis of 2007–8, followed by a period of recession around the world and, more importantly, the European sovereign debt crisis which peaked around 2011–12; see Petrick and Kloss, 2013; Van der Sluis and Parlińska, 2013). As the number of observations over time is not large, applying time series analysis techniques (e.g., dynamic panels) would not make much sense. Hence, we consider time modeling strategies based on production frontiers in m_1–m_3 and analyze their estimates, which lead to the following additional specifications:

- m_4: by analyzing time effects (λ) in m_3 one can see that there were two considerable shocks in the EU that affected crop production: 2008 and 2012–13 (see Figure A1 and Table A3 in Appendix A); model m_4 is thus model m_1 with a time effect (λ_{cr}) added to indicate these years.
- m_5: by analyzing m_4 (and m_1) one can notice that there are at least three regression coefficients, which are statistically insignificant: $\beta_{1,4}, \beta_{2,4}, \gamma_4$ (see Table A3; Appendix A); thus, we discard them in m_5.
- m_6: by analyzing m_5 we can notice that there is one more parameter that may be statistically insignificant: γ_2; we discard this parameter in m_6.

Model comparison for crop production is summarized in Table 2. Specifications m_1–m_6 do not change the key results in any substantial way, i.e., skewness of OLS residuals remains positive, elasticity of land is negative at that sample mean and average technical change is negative, though the positive estimate of parameter γ_1 next to t squared indicates that this negative effect diminishes in time (see Table A3). Specification m_6 decisively provides the best model fit and we find no other combination based on m_0–m_3 that would increase the Bayes factor. Hence, we continue our investigation with production function m_6. Appendix B provides additional results for production frontier m_0, which show that further results are not driven by the choice of a particular frontier parametrization.

We should also note that, in theory, one could conduct a fully automated Bayesian Model Selection (in terms of covariate selection) by searching all $L = 2^{34} - 2$ possible production frontier specifications. However, estimating that many models with the prior structure presented in

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Table 2. Production frontier specification comparison

Model	BF	ln(p(y))	ln(ML)	BIC	σ_v	Skew.	ATC	Production elasticities at mean level of inputs			
								Build. and Machin.	Labor	Materials	Land
$\mathbf{m_0}$	1.6E-60	−497.83	−380.1	902.91	0.2641 (0.0028)	0.349	−0.012 (0.001)	0.010 (0.010)	0.150 (0.010)	0.840 (0.010)	−0.070 (0.010)
$\mathbf{m_1}$	3.4E-62	−438.28	−281.26	562.51	0.2604 (0.0028)	0.371	−0.011 (0.001)	0.094 (0.007)	0.150 (0.010)	0.835 (0.009)	−0.070 (0.008)
$\mathbf{m_2}$	3.2E-58	−444.78	−317.35	634.69	0.2551 (0.0027)	0.376	−0.011 (0.001)	0.095 (0.007)	0.154 (0.010)	0.837 (0.009)	−0.073 (0.008)
$\mathbf{m_3}$	2.3E-32	−381.71	−206.24	412.48	0.2551 (0.0027)	0.432	−0.097 (0.016)	0.089 (0.007)	0.154 (0.010)	0.850 (0.009)	−0.083 (0.008)
$\mathbf{m_4}$	3.5E-35	−386.36	−223.46	446.92	0.2551 (0.0027)	0.394	−0.011 (0.001)	0.093 (0.007)	0.150 (0.010)	0.840 (0.009)	−0.075 (0.008)
$\mathbf{m_5}$	8.7E-08	−370.74	−225.31	450.63	0.2552 (0.0027)	0.396	−0.011 (0.001)	0.092 (0.007)	0.150 (0.009)	0.841 (0.009)	−0.075 (0.008)
$\mathbf{m_6}$	1	−365.45	−227.35	614.30	0.2604 (0.0028)	0.409	−0.011 (0.001)	0.091 (0.007)	0.149 (0.009)	0.842 (0.009)	−0.074 (0.008)

Notes: ATC stands for average (annual) technical change in the analyzed period; for model m_3 ATC is calculated as the average estimate of time effects λ_t; for the remaining models it is $\partial y/\partial t$; BF stands for Bayes factor; Bayes factors are calculated as in favor (BF $<$ 1) or against (BF $>$ 1) specification m_6; the highest BF value indicates the best specification; results based on non-SF specification.

Section 3 is currently not feasible in an acceptable timeframe. Furthermore, in this study we have found differences in marginal likelihoods (p(y)) between frontier specifications to be far greater than differences between error specifications (compare: ln(p(y)) between Tables 2, 3 and Table B1 in Appendix B). So, the final L-model comparison would still be dominated by models with the best frontier specification.

As mentioned, we obtain a negative value for the mean production elasticity of land in all the abovementioned constructions of the frontier (see Table 2). Though this may seem worrying, such result is not rare in agricultural economics (see, e.g., Amsler et al., 2016; Djokoto, 2012; Fulginiti and Perrin, 1998; Latruffe et al., 2017). There are several reasons for that. First, it has been indicated in the previous section that land can be viewed as a quasi-fixed factor in the short-run, and the negative sign can suggest differences in land quality or surplus land. The problem may be especially persistent in aggregated data where a representative farm is defined by the group of crop farms located in the same region and belonging to one of the six size classes. An increase in the utilized land may take place when, in the same region, a farm buys or leases land from another farm of a different economic size. Alternatively, a horticulture farm can increase crop production so much that it classifies into a new group in the following year. Another reason may be more indirect, e.g., via government or EU subsidies. As these are often based on land size, they may act as a disincentive to sell excessive land leading to surplus land, especially in case of medium and large farms. A quick analysis of individual representative farms reveals that positive values for elasticity of land are predominantly found in very small or small farms (i.e., farm size = 1: 57% farms have land elasticities above 0; size = 2: 31%; size = 3: 10%; size 4: 3%; size 5–6: 0%).

Given the abovementioned results, we have decided on a different approach to further refine the model. Under the best frontier specification (m_6) we focus on the "black box" of the stochastic frontier analysis, namely the underlying stochastic assumptions about the standard two-component compound error. Following Makieła and Mazur (2022), we generalize these assumptions and estimate the generalized *t*-generalized beta of the second kind model (GT-GB2).

Results based on this model and its derivatives are also reported in Table 3. Even though GT-GB2 has been primarily established as a platform for model search (as it is rather heavily parameterized) it still decisively outperforms the three models discussed so far (N-HN, N-EX, non-SF). In fact, the Bayes factor is about 8.4×10^{25} times more in favor of this specification than the assumption of equal relative efficiency (i.e., the non-SF model). This is clear evidence that there is in fact substantial, nonnegligible inefficiency in the analyzed process, which reveals itself once sufficient generalization of the compound error is made. Our further investigation into the optimal stochastic structure indicates that the best model is obtained when the random term follows Student's t distribution, and inefficiency follows half-generalized-t distribution, we label this the T-HGT model. The calculated Bayes factor is about 1.8×10^{28} times more in favor of T-HGT than the non-SF and it is the highest value of all GT-GB2's nested cases we have considered.

We notice two key contributors to this outcome. First, the random disturbance is clearly fat-tailed with the estimate of the degrees of freedom being around 6 for the best models in the ranking. This may indicate that there are outliers in the sample (Stead et al., 2018), and Student's t distribution seems adequate for such cases (Wheat et al., 2019). Second, inefficiency distribution is substantially "flattened" around the mode. This feature of the distribution is governed by parameter ψ_u, which in this case has a relatively high estimate. We find that all models that show substantial inefficiency differences have high marginal likelihoods and inefficiency distribution with estimable (and relatively high) parameter ψ_u.

When comparing efficiency scores from the best model to those from standard SF models (e.g., N-HN, N-EX) we find that, at the same time, they can be considered either as quite similar or as substantially different. This depends on their prospective use. That is, if the goal of a study is "only" to rank objects then we note that there is 0.926 correlation between efficiency estimates in T-HGT and N-HN (0.897 for T-HGT vs. N-EX; see Table 4). However, we should also point out that there is 0.913 correlation between efficiencies estimates from the simple Corrected Ordinary Least Squares (COLS) and N-HN (0.868 for COLS vs. N-EX). Hence, if we only need to rank the representative farms based on their efficiencies then there is no substantial gain in moving beyond the most simplistic methods like COLS. However, if the goal is to put meaningful interpretation to the efficiency scores and, especially, to their differences then the results differ quite dramatically. Figure 1 shows histograms of efficiencies scores in N-HN, N-EX and T-HGT. The differences are evident, i.e., the advantage of the best SF model is in its ability to (i) better assess distances between individual efficiency scores, (ii) better assess their spread as well as to (iii) better identify average efficiency in the sample. This in turn may produce considerably different outcomes, especially for policymaking whenever exact (in)efficiency values are used by the regulatory agency.

5.2. Regional-level efficiency analysis of crop farming in the EU

The spatial spread of efficiency levels among the EU regions is summarized on the map in Figure 2. We note that high efficiency levels cluster around the Benelux and the Mediterranean regions, and low efficiency levels cluster in the regions of Eastern and North-Eastern EU.

Efficiency changes over time are summarized in Figure 3 and 4, while detailed results are provided in Table 5. Given the goals of the EU's Cohesion Policy, we would expect regions of low efficiency, especially from the new Member States, to gain efficiency. However, the results presented on the maps in Figures 2 and 3 are not in line with this concept. The least productive regions reported in Figure 2 do not catch up over time. In fact, on average the old Member States have been dominating over the new ones in terms of efficiency throughout the analyzed period. The technical efficiency gap between the two groups has not closed, it might have even slightly grown over time (0.028 efficiency gap in 2004 vs. 0.031 gap in 2017; see Figure 4). Hence, the more efficient farms are generally those in the regions of the old EU, and despite the goals of the EU's Cohesion Policy this has not changed.

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Table 3. Basic statistics and posterior estimates of the stochastic parameters in SF models

Model	BF	ln(p(y)	ln(ML)	BIC	σ_u	σ_v	τ_u	ψ_u	ψ_v	ν_v	ν_u	av.eff
non-SF	1	−365.45	−227.35	614.3		0.2552 (0.0027)						1 (-)
N-HN	4.6E-03	−370.83	−230.81	629.6	0.0671 (0.0193)	0.252 (0.0033)						0.9447 (0.0432)
N-EX	9.3E-05	−374.73	−234.11	636.2	0.0424 (0.01)	0.2519 (0.0031)						0.9555 (0.0433)
T-HGT	1.8E + 2	−300.40	−161.35	515.9	0.3112 (0.1005)	0.1838 (0.0298)		36.4506 (29.7644)		5.8952 (1.7299)	40.0229 (30.8338)	0.8008 (0.1002)
GT-HGED	5.7E + 2	−301.54	−161.21	515.6	0.3383 (0.1065)	0.1808 (0.0294)		41.0351 (35.5449)	2.6218 (0.9151)	4.9648 (2.2517)		0.7889 (0.1031)
GT-HGT	2.0E + 2	−302.56	−161.29	524.2	0.316 (0.0947)	0.189 (0.021)		45.6647 (32.5463	2.2795 (0.7647)	5.8472 (2.7429)	39.8242 (31.6856)	0.8036 (0.0966)
T-HGED	4.8E + 2	−304.01	−161.35	507.5	0.3327 (0.0708)	0.1889 (0.0143)		44.5157 (31.7271)		6.1081 (1.088)		0.799 (0.0885)
GT-GG	3.1E + 2	−304.45	−161.24	524.1	0.2525 (0.0309)	0.2035 (0.0076)	0.7686 (0.1622)	42.1672 (36.6649)	2.9658 (1.5617)	5.218 (1.8674)		0.8668 (0.0742)
GT-GB2	8.4E + 2	−305.76	−161.25	532.5	0.0128 (0.0132)	0.2232 (0.0045)	0.6241 (0.2636)	5.9925 (4.263)	2.349 (0.2098)	6.1849 (1.0586)	5.3553 (7.7328)	0.9909 (0.018)
T-HN	1.8E + 2	−307.30	−165.22	506.8	0.1007 (0.0283)	0.2119 (0.0073)				7.5585 (0.9699)		0.9118 (0.0634)
T-HT	1.4E + 2	−307.52	−165.22	515.2	0.0897 (0.0278)	0.2133 (0.0072)				7.728 (1.0203)	42.7777 (33.2717)	0.9192 (0.0614)
LP-HGED	1.2E + 2	−307.71	−166.80	518.4	0.4188 (0.0402)	0.1431 (0.0093)		19.4138 (20.6443)		53.058 (32.2605)		0.7122 (0.0866)
GT-HN	7.7E + 2	−308.15	−163.75	512.3	0.094 (0.0296)	0.2149 (0.0077)			2.3089 (0.2395)	6.1627 (1.2926)		0.9186 (0.0612)

(*Continued*)

Table 3. (*Continued*)

Model	BF	ln(p(y))	ln(ML)	BIC	σ_u	σ_v	τ_u	ψ_u	ψ_v	ν_v	ν_u	av.eff
GT-HT	4.4E + 24	−308.69	−163.75	520.7	0.0853 (0.0273)	0.2156 (0.0069)			2.3151 (0.3201)	6.2038 (1.2993)	44.7803 (33.6595	0.9241 (0.0584)
LP-HGT	2.2E + 24	−309.42	−166.80	526.8	0.4238 (0.0382)	0.1442 (0.0076)		29.591 (29.029)		54.4943 (32.0403)	45.3163 (32.6543)	0.7128 (0.0863)
GT-EXP	2.7E + 2	−311.49	−166.61	518.0	0.0524 (0.0124)	0.2164 (0.0064)			2.3686 (0.4915)	6.1439 (1.3318)		0.9427 (0.0535)
LP-HN	1.1E + 1	−328.54	−184.66	545.7	0.221 (0.0106)	0.1554 (0.005)				83.4432 (39.4487)		0.785 (0.0983)
LP-HT	7.4E + 1	−331.21	−184.66	554.1	0.2152 (0.0108)	0.156 (0.0052)				84.6997 (42.506)	81.8482 (40.1932)	0.7878 (0.0987)

Notes: Bayes factors (BF) are calculated as in favor (BF $<$ 1) or against (BF $>$ 1) the non-SF model (i.e., model that assumes equal relative efficiency of representative farms); the best model (T-HGT) has the highest Bayes factor; all models are based on the same frontier specification (m_6).

Table 4. Correlation coefficients between efficiency estimates in COLS, H-NH, N-EX, and T-HGT

	COLS	N-HN	N-EX	T-HGT
COLS	1	0.913	0.868	0.847
N-HN	0.913	1	0.973	0.926
N-EX	0.868	0.973	1	0.897
T-HGT	0.847	0.926	0.897	1

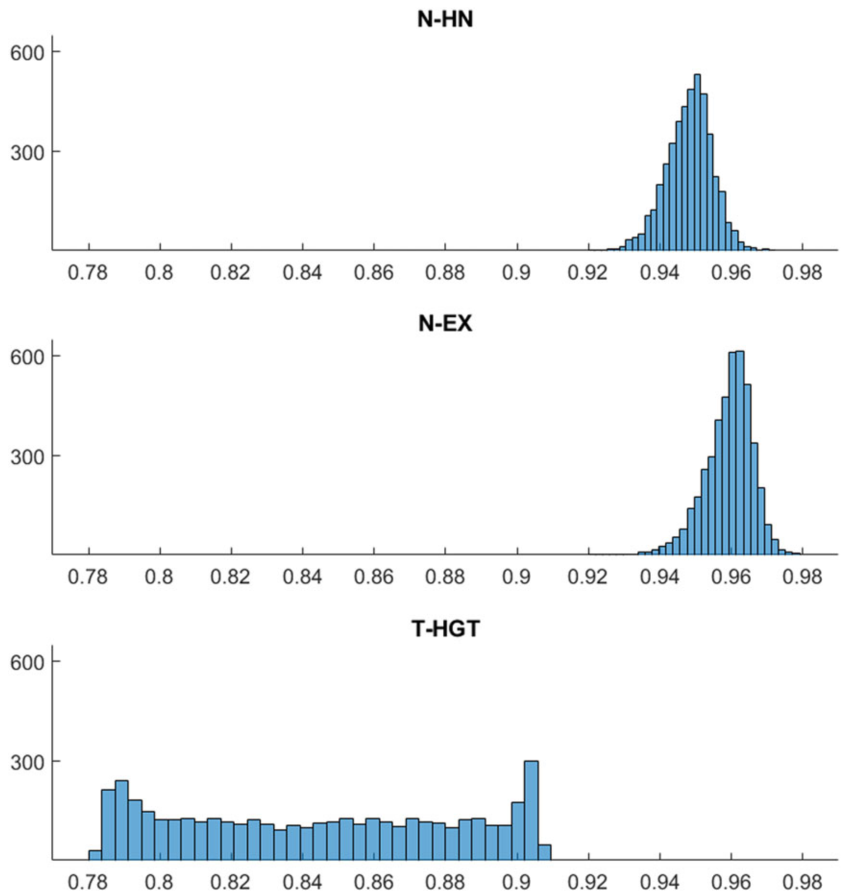

Figure 1. Histograms of efficiency estimates for normal-half-normal, normal-exponential and *t*-half generalized *t* models.

Substantial efficiency gains are more common in the old EU regions, with Denmark especially standing out. Like in Barnes and Revoredo-Giha (2011), we notice low efficiency at the beginning of the analyzed period in Denmark (see Table 5). However, Danish regions have been increasing their efficiency rapidly and now Denmark is among the most efficient countries in terms of crop farming in the EU. The new EU Member States (i.e., from 2004 expansion onwards) have been struggling with relatively low efficiency throughout analyzed period and did not manage to catch up. This is especially the case for Poland and Malta, which may be a sign of failures of agriculture policies in those countries.

Efficiency results based on farm size are summarized in Table 6. For the entire EU (the last row), we notice that large farms are generally slightly more efficient. This is particularly the case in

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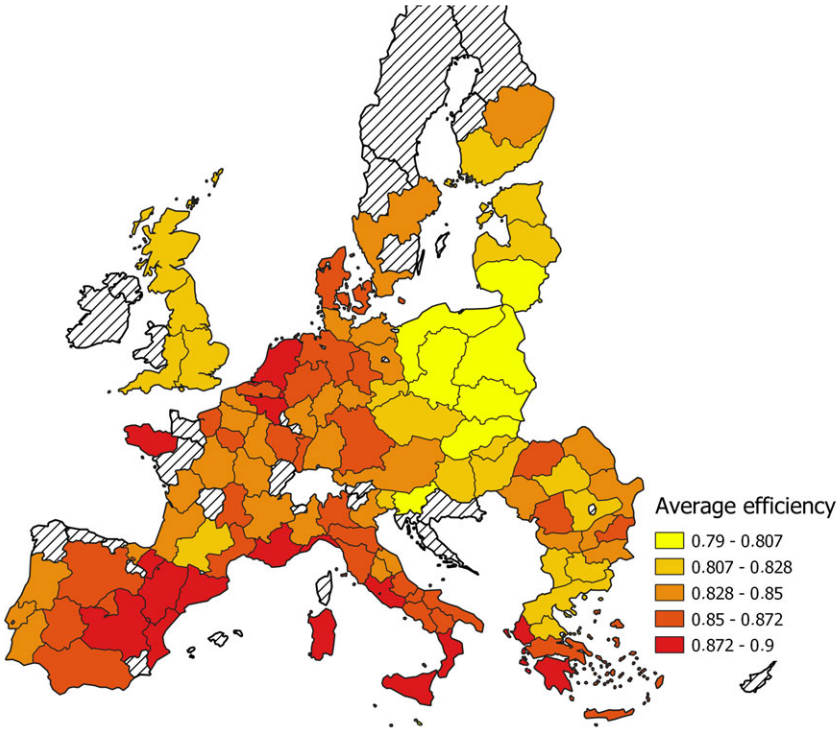

Figure 2. Map of high and low efficiency scores in crop farming in the EU at the regional level.

countries with relatively high efficiency (e.g., Spain, the Netherlands, Denmark, Italy). For countries with low efficiency (e.g., Poland, Estonia, Lithuania and Portugal) the tendency is rather opposite, i.e., small farms tend to be slightly more efficient. Also, this trend is not linear, i.e., middle-sized farms (i.e., farms of size "3") are usually the least efficient, regardless of country's average efficiency. This result is line with previous findings about a U-shaped correspondence between the farm size and its productive efficiency (Debrah and Adanu, 2022).

6. Discussion

6.1. Technical efficiency of crop farms in the EU

We find that the representative farms with relatively high efficiency usually cluster in the regions of the Benelux and the Mediterranean Sea, which is no doubt due to favorable geographic location for crop farming. This is in line with Schils et al. (2018) who also find that Northern France, Belgium and the Netherlands have the most effective regions in terms of crop-output per hectare. Though the authors do not find Mediterranean regions as effective as we do, this may be because Schils et al. (2018) did not consider non-greenhouse vegetable cultivation, at which Mediterranean regions excel (Eurostat, 2022). Furthermore, we find that efficiency gains over time are more often witnessed in the regions of the old EU Member States rather than in the new ones. This would indicate that, on average, the new Member States are not catching up with the old EU. There is a rather persistent (if not growing) difference in terms of technical efficiency over time between the two country groups. This is particularly worrying because we would expect the gap between the old and the new to get smaller because of the EU's Cohesion Policy. Obviously, this is not the case. At this point it is hard to tell if the Cohesion Policy has any significant effect on crop farming in the EU, but the results do not support the notion that the EU gets any more "cohesive" in terms of

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Table 5. Efficiency estimates (posterior means) over time at the country and the EU levels

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Avg.
CZE	0.795	0.818	0.798	0.810	0.791	0.822	0.832	0.809	0.832	0.811	0.803	0.802	0.820	0.800	0.810
BEL	0.874	0.875	0.830	0.814	0.836	0.865	0.899	0.839	0.876	0.859	0.904	0.857	0.839	0.867	0.860
BGR				0.822	0.826	0.833	0.862	0.850	0.847	0.859	0.822	0.825	0.831	0.844	0.839
DAN	0.786	0.803	0.796	0.864	0.827	0.843	0.899	0.893	0.903	0.898	0.894	0.893	0.893	0.898	0.863
DEU	0.859	0.893	0.870	0.823	0.818	0.877	0.857	0.809	0.842	0.836	0.842	0.847	0.864	0.858	0.849
ELL	0.842	0.867	0.834	0.830	0.826	0.845	0.856	0.846	0.857	0.879	0.834	0.822	0.848	0.848	0.845
ESP	0.869	0.849	0.878	0.879	0.857	0.866	0.884	0.870	0.867	0.876	0.858	0.852	0.878	0.874	0.868
EST	0.795	0.825	0.788	0.811	0.858	0.833	0.794	0.801	0.817	0.834	0.813	0.861	0.840	0.868	0.826
FRA	0.869	0.867	0.859	0.842	0.868	0.836	0.841	0.852	0.852	0.838	0.832	0.831	0.822	0.858	0.848
HUN	0.824	0.838	0.839	0.793	0.837	0.803	0.820	0.811	0.793	0.800	0.807	0.804	0.843	0.828	0.817
ITA	0.829	0.868	0.853	0.862	0.843	0.853	0.879	0.862	0.872	0.868	0.858	0.865	0.868	0.865	0.860
LTU	0.796	0.817	0.788	0.805	0.808	0.819	0.821	0.799	0.824	0.802	0.793	0.805	0.789	0.803	0.805
LVA	0.802	0.793	0.805	0.793	0.819	0.798	0.791	0.789	0.819	0.809	0.824	0.839	0.826	0.834	0.811
MLT	0.801	0.795	0.825	0.803	0.837	0.794	0.789	0.790	0.795	0.793	0.811	0.797	0.799	0.786	0.801
NED	0.798	0.881	0.868	0.889	0.903	0.904	0.900	0.893	0.904	0.889	0.889	0.898	0.864	0.866	0.882
OST	0.868	0.869	0.858	0.822	0.895	0.853	0.816	0.859	0.829	0.834	0.844	0.828	0.862	0.824	0.847
POL	0.793	0.817	0.805	0.795	0.789	0.793	0.805	0.787	0.791	0.788	0.788	0.791	0.793	0.792	0.795
POR	0.805	0.814	0.859	0.831	0.844	0.842	0.831	0.838	0.856	0.856	0.839	0.838	0.831	0.841	0.838
ROU				0.802	0.828	0.835	0.850	0.833	0.838	0.842	0.842	0.813	0.821	0.855	0.835
SUO	0.816	0.805	0.825	0.852	0.799	0.788	0.856	0.809	0.804	0.795	0.838	0.849	0.824	0.861	0.823
SVE	0.828	0.857	0.840	0.835	0.851	0.808	0.833	0.821	0.828	0.830	0.807	0.822	0.840	0.829	0.831
SVK	0.790	0.843	0.788	0.792	0.797	0.797	0.802	0.820	0.813	0.844	0.791	0.793	0.829	0.812	0.807
SVN			0.788	0.789	0.786	0.783	0.791	0.789	0.789	0.793	0.800	0.802	0.790	0.791	0.792
UKI	0.794	0.849	0.864	0.840	0.822	0.805	0.854	0.810	0.807	0.797	0.794	0.810	0.823	0.825	0.822
EU	0.835	0.856	0.847	0.839	0.836	0.841	0.854	0.839	0.846	0.846	0.836	0.835	0.842	0.850	0.843

Note: Three-letter country codes are according to FADN nomenclature.

productive efficiency of crop farming (Baráth and Fertő, 2017). In this regard our results contradict the findings of Garrone et al. (2019), Kijek et al. (2019) and Quiroga et al. (2017). However, it should be noted that our study was conducted using representative farms of one agricultural sector and at a regional level. Garrone et al. (2019) and Quiroga et al. (2017) analyzed entire agriculture industries (i.e., combined agricultural sectors), while Baráth and Fertő (2017) and Kijek et al. (2019) analyzed the country level productivity and entire agriculture industries.

We find that the least efficient representative farms are usually of medium size. This is line with Debrah and Adanu (2022) who also find a U-shaped dependency between the farm size and its efficiency. However, we also find that while large farms are often the most efficient types of farms in technically efficient regions, they tend to be among the least efficient types in low efficiency regions. Since the notion that large crop farms are usually more productive/efficient than others is quite common in the literature (Paul et al., 2004), this finding may indicate inadequate development of large farms in those regions. This feature is especially visible in the Eastern

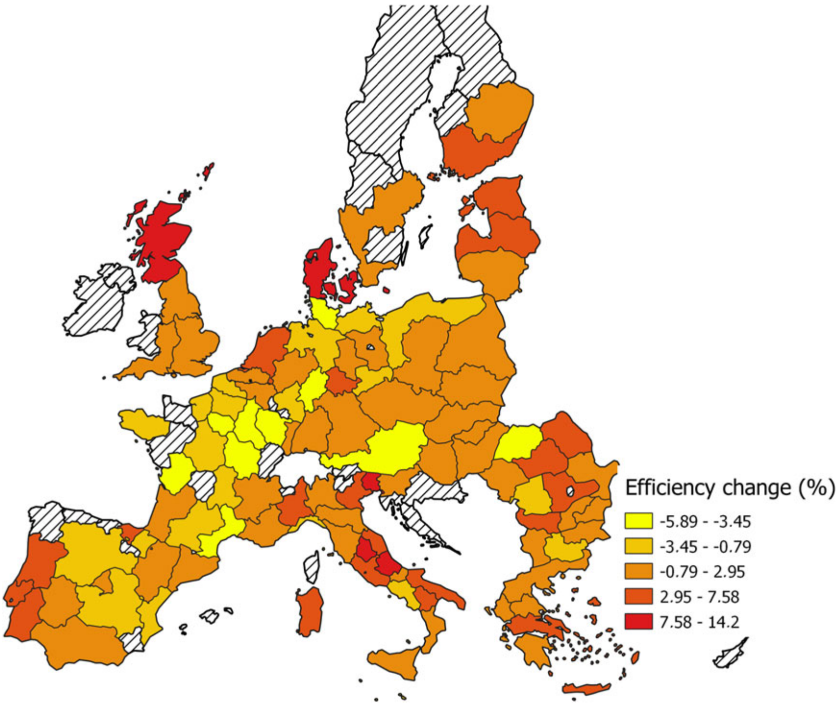

Figure 3. Map of high and low efficiency change in crop farming in the EU at the regional level.

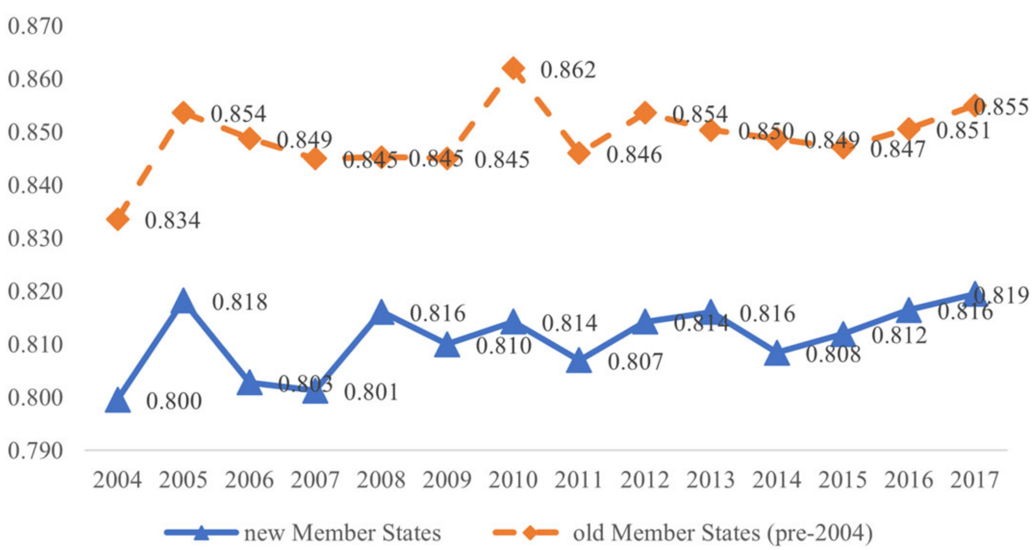

Figure 4. Average efficiency levels in the “new” and “old” (pre-2004) Member States over time.

European regions, and it may have its roots in the decades of communism that these economies suffered through. Before the economic transformation that began in 1990s, large farms in those countries were state-owned, terribly mismanaged, underdeveloped and worked in a centrally planned economy. It seems that not all this inefficiency is gone. The low efficiency of large farms may also be the reason why those countries in which such farms operate have rather low overall

Table 6. Efficiency estimates across farm size (1–6) at the country and the EU level

	1	2	3	4	5	6	Avg.
CZE		0.810	0.801	0.803	0.816	0.820	0.810
BEL				0.844	0.868	0.845	0.860
BGR	0.834	0.828	0.818	0.830	0.841	0.871	0.839
DAN		0.857	0.859	0.860	0.871	0.866	0.863
DEU			0.849	0.843	0.849	0.855	0.849
ELL	0.824	0.846	0.855	0.857	0.829		0.845
ESP	0.864	0.864	0.867	0.868	0.877	0.898	0.868
EST	0.878	0.830	0.807	0.825	0.830	0.827	0.826
FRA			0.813	0.840	0.859	0.859	0.848
HUN	0.809	0.801	0.805	0.815	0.820	0.853	0.817
ITA	0.844	0.858	0.861	0.863	0.867	0.865	0.860
LTU	0.819	0.804	0.793	0.798	0.804	0.818	0.805
LVA	0.839	0.805	0.801	0.802	0.810	0.843	0.811
MLT	0.804	0.807	0.793				0.801
NED			0.848	0.890	0.882	0.885	0.882
OST		0.845	0.839	0.848	0.856		0.847
POL	0.805	0.795	0.792	0.788	0.793	0.799	0.795
POR	0.875	0.849	0.818	0.832	0.816		0.838
ROU	0.826	0.833	0.828	0.828	0.842	0.871	0.835
SUO		0.832	0.812	0.820	0.818		0.823
SVE		0.826	0.815	0.831	0.851		0.831
SVK		0.811	0.825	0.793	0.807	0.804	0.807
SVN	0.798	0.788	0.793	0.791	0.793		0.792
UKI			0.822	0.816	0.820	0.839	0.822
EU	0.832	0.841	0.840	0.842	0.849	0.852	0.843

efficiency. This result seems to be quite interesting because it refers to the results of Foster and Rosenzweig (2022) that explain the U-shaped relationship between farm productivity and farm scale in developing-country agriculture. The authors point out in their conclusions that there are often barriers to agricultural productivity growth that may not be easily overcome through individual investment decisions or cross-country technology transfer. This may also apply to post-communist countries, according to the presented findings.

6.2. Model specification and its consequences in analyzing efficiency

Initial analysis based on popular SF models indicates that the most adequate model is the one that assumes full relative efficiency of representative crop farms in the EU. This contrasts with the general knowledge about crop farming. Despite a relatively large number of observations and adequately defined technology frontier the "simple," non-SF model seems more appropriate given

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data than "classic" SF models, like normal-half-normal or normal-exponential. Augmenting the frontier does not change the outcome. The obtained efficiency scores are very high with hardly any variation, which promotes the notion of full relative efficiency. Hence, the initial analysis leaves us with results, which are hard to accept by empirics. The extended analysis based on GT-GB2 model provides results, which are not only superior in terms of statistical fit but also much more reasonable. That is, the optimal model (T-HGT) identifies substantial, nonnegligible differences in productive efficiency of crop farms in the EU. This is somewhat different to findings in Makieła and Mazur (2022) who note that the best models given data show relatively high average efficiency with a relatively low spread between efficiency estimates. Their study, however, did not cover cases with "wrong" skewness. We find that such unrealistically high efficiency scores can be due to outliers and over-restrictive assumptions about the distribution of the compound error term, which may lead to "wrong" skewness of the OLS residuals. Staniszewski and Borychowski (2020) also show that one can observe unrealistically high efficiency results even when OLS residuals are "properly" skewed. Hence, the problem of unrealistically high efficiency estimates likely goes beyond just "wrong" skewness. We believe that generalizing the stochastic assumptions about the inefficiency and the error term may be instrumental in solving the problem.

Apart from assessing the average efficiency levels of representative crop farms in the EU, the goal has been (i) to assess the changes in efficiency of crop farming in the EU over time, and (ii) to provide a very broad cross-region efficiency benchmark of crop farming in the EU. For this reason, we allow efficiency components to be both time and object specific. This can be viewed in terms of a simple "pooled" estimator, though we should note that the standard SF model for panel data with persistent inefficiency is a special case (restriction) of this model. We do not allow for such a restriction as it would preclude temporal analysis of efficiency, not to mention that assuming time-invariant efficiency over a 14-year period is rather unrealistic. An interesting option might be to incorporate an idea by Cuesta (2000), who generalizes the model by Battese and Coelli (1992), into the GT-GB2 framework. This way inefficiency could vary over time while significantly reducing the number of parameters and latent variables. Also, if there is knowledge about additional factors that impact the observed inefficiency differences one could allow the distribution of inefficiency to depend on some exogenous factors, similarly to Battese and Coelli (1995) and Koop et al. (2000); see also Makieła and Mazur (2022). It would surely allow for additional model heterogeneity – or flexibility – this time via inefficiency distribution. Since this extension effectively boils down to adding more explanatory variables into the model (via parametrizing the location/scale/shape parameters of inefficiency distribution) it remains uncertain if this would address the key problem, i.e., wrong skewness.

We do not impose panel data structure similar to the true random effects or generalized true random effects models (Makieła, 2017; Pisulewski and Marzec, 2022). Apart from computational considerations (e.g., unbalanced panel, increased identification problems in SF models due to more complex error terms) we should note that such frontier heterogeneity would make cross-section efficiency benchmark much more difficult as every farm would have a slightly different frontier. Also, employing methodologies that account for heterogeneity (i.e., random coefficient SF model and "true" fixed effects SF model) to FADN data, so far, has not solved the key problem, i.e., very high efficiency among farms and hardly any variation (Marzec and Pisulewski, 2020; Staniszewski and Borychowski, 2020). Finally, one could argue that determining heterogeneity in a benchmark study for performance-based policymaking is as much an academic as it is regulatory policy.

Our comparison (i.e., model testing) is based on Bayes factors and implicitly assumes equal prior odds for all compound error specifications under evaluation (i.e., we assume that every model is equally probable before the data are revealed). It is a common practice in Bayesian inference to incorporate some prior knowledge into the analysis. For example, following Copernican principle of simplicity Osiewalski and Steel (1993) propose to favor parsimonious models via the following prior: $p(M_i) \propto 2^{-k}$, where M_i is a given model and k is its number of parameters to be estimated. We should point out that such prior would only strengthen our conclusion about the best model (T-HGT), especially with relation to models, which have comparable explanatory power but more parameters (i.e., GT-HGT, GT-GB2, GT-HGED).

7. Conclusions

The goal of this research was to analyze efficiency of crop farming in the EU based on publicly available data on representative farms provided by FADN. We have found that wrong skewness shows up in FADN data even though there is evidence in the literature that crop farming is not equally efficiency across Europe. We have found that augmenting the production technology does not remedy the problem, which is in line with previous studies that used FADN data. For this reason, we have re-examined the "black box" of SF models, which is the set of stochastic assumptions about the compound error term ε. To find the best model (in terms of adequate specification of the error term ε) given data we have performed a set of rigorous model specification tests using exact Bayesian methods (marginal likelihoods, Bayes factors), especially with respect to the standard normal-half-normal and normal-exponential models. Our motivation comes from the fact that while the choice of explanatory variables and frontier parametrization in benchmark studies are often based on some theoretical considerations or dictated by a regulatory agency, the stochastic assumptions about the compound error are usually the result of a computational convenience. Hence, the proposed solution may be particularly appealing for cases where altering the frontier specification may not be a desired course of action (e.g., regulatory requirements), or it does not remedy the problem, or both.

Subsequent studies that used FADN data, as well as our own initial analysis based on standard SF specifications indicate full, or almost full, relative efficiency of crop farming in the EU. A more in-depth analysis based on the framework proposed by Makieła and Mazur (2022) has shown that such results are likely due to over-restrictive distributional assumptions about the compound error. It appears that the problem in contemporary SF models may be due to unfit distributional assumptions about the compound error. Generalizations in such cases, like the GT-GB2 model, are necessary. Relying on simple measures like skewness of OLS residuals (along with embedded normality assumptions) to identify inefficiency component in the data may be inadequate, at least for this type of application. Also, it is worth noting that the analysis could easily be extended to consider variable (covariate) selection or frontier parametrization problems (individual effects, persistent and transient inefficiencies, other forms of heterogeneity). The downside would be, apart from computational considerations, that the researcher would be left with a very large number of specifications to consider and efficiency scores that may not be easily comparable.

The best model given data has been determined using exact Bayesian model selection methods based on Bayes factors. Efficiency rankings are similar in all SF models considered. However, the best model given data (t-half-generalized t) identifies substantial, nonnegligible differences in productive efficiency of representative crop farms. We find that while large representative farms are often the most efficient types of farms in technically efficient regions, they tend to be among the least efficient types in low efficiency regions. This finding may indicate inadequate development of large farms in those regions. We also find that regions of the Eastern European countries (i.e., East by North-East) are often the least efficient and that, more importantly, they are not catching up with the "old" EU over time. Though the reason for this remains unclear the results are conclusive. The EU's Cohesion Policy is not producing the expected outcome in the sector of crop farming as the "new" regions are not catching up in terms of productive efficiency.

There are many ways, in which benchmark analyses, such as this one, may help enhance performance of crop farming in the EU. First, a credible efficiency analysis is the cornerstone of a successful performance-based policymaking with incentive mechanisms tied to agriculture subsidies. Similar mechanisms are already in place in other markets (e.g., energy production and distribution), and SFA can be later used to assess the impact of such policy designs. Second, the results can be used to monitor the state of the common European agriculture market of crop farming and help pinpoint sub-optimal regions and farms. Of course, such sub-optimality may be due to a number of reasons sometimes beyond farmers' control (climate, soils quality, country-level legislative barriers etc.). These reasons should be assessed on a case-by-case basis. Third, from the perspective of time series analysis efficiency change is usually the first component of economic growth to react to any macroeconomic disruptions. Hence, provided that such a benchmark is done on a regular basis and with up-to-data data, it can be used as a warning tool for, e.g., pending market crises.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/aae.2025.1.

Data availability statement. The data that support the findings of this study are publicly available from the Farm Accountancy Data Network (FADN) at https://agridata.ec.europa.eu/extensions/FarmEconomyFocus/FADNDatabase.html.

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